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Research paper

Investigating the Factors Affecting the Intention to Use AI Chatbots in STEM Education App: A Hybrid Structural Equation Modelling and Artificial Neural Network

Morshada Khanam Mim [1]*, Mst. Tahmina Jerin Arju[1], Mahady Hasan[2], Farzana Sadia[1], Shipra Banik[1]

[1] *Independent University*, BANGLADESH
[2] *Asian University for Women,* BANGLADESH

***Corresponding Author:** 2432637@iub.edu.bd

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ABSTRACT

This study explores the impact of Artificial Intelligence (AI)-powered applications in Science, Technology, Engineering, and Mathematics (STEM) education, emphasizing their role in improving students' problem-solving skills and self-efficacy. It examines how personal factors such as ICT self-efficacy and self-directed learning (SDL), along with technological aspects like perceived ease of use (PEU) and perceived convenience (PC), shape students' engagement with AI-driven tools. Using a quantitative method, survey data were collected from 117 students during February–March 2025. The research employed the Structured Predictive Latent Semantic System (SPLSS) model and Artificial Neural Network (ANN), validated through Structural Equation Modeling (SEM), to ensure reliability and predictive accuracy. Results show that AI tools significantly enhance problem-solving and self-efficacy. PC and intention to use were strong predictors of chatbot utilization, while ICT self-efficacy and PEU influenced attitudes and behavioral intentions. Importance-Performance Map Analysis (IPMA) revealed convenience as most impactful, and self-efficacy as least. All hypotheses were supported, confirming the model's robustness. The study concludes that AI-driven applications create personalized, engaging, and confidence-boosting STEM learning experiences, highlighting the need for user-friendly, contextually adaptive AI tools and suggesting future research on long-term impacts and scalability for inclusive STEM education.

Keywords: SPLSS model, problem-solving skills, ICT self-efficacy, AI-powered STEM education, ANN model

STEM approach centres on down to earth scenarios and cultivates imaginative learning through problem-solving. It prioritizes dynamic learning over memorization or conventional strategies by joining real-world issues and empowering understudies to discover arrangements (Tashtoush et al., 2024). Successful perusing comprehension progresses students' problem-solving, investigation, and higher-order considering capacities, which are basic for STEM instruction and advancement (Islam et al., 2026). The integration of innovation, online assets, and versatile learning apparatuses can improve students' perusing capacities and engagement, supporting superior learning results in STEM instruction. STEM instructing with language-support hones makes a difference all sort of understudies' progress both interest and communication aptitudes in classrooms. Advanced learning materials and technology-based instruction can diminish dialect boundaries and make more available learning openings for assorted understudies in STEM areas (Dogutas, 2025). AI in STEM instruction can progress educating, learning, and investigate through versatile learning frameworks, cleverly coaching, computerized input, and information analytics that bolster students' scholarly improvement. It ought to back instead of replace teachers, making a difference STEM instruction gotten to be more personalized, proficient, and human-centered. AI-based innovations in higher instruction can fortify problem-solving, advancement, and basic considering abilities, which are basic components of STEM instruction (Tuanpusa et al., 2026).

STEM education is being adapted by AI by offering personalized learning experiences that help students improve their problem-solving skills and boost self-efficacy. In recent decades, many technological developments have raised. Traditional teaching methods often fail to address individual learning needs, making it challenging for students to develop confidence in tackling complex problems (Esiyok et al., 2025). The increasing incorporation of AI in educational settings, many STEM students struggle with problem-solving due to a lack of personalized learning approaches (Yu et al., 2025). Students' self-efficacy in STEM subjects is often low, leading to decreased motivation and academic performance. Existing AI-powered learning tools have yet to be fully evaluated for their effectiveness in addressing these challenges (Obiwuru, 2024). In this study focus on the problems and find the ways how these problems can be solved. This study goals to examine the part of AI-powered STEM education applications in enhancing students' analytical and reasoning capabilities in addressing problems and self-efficacy. Using the SPLSS model, the research evaluates the efficiency of AI-powered learning tools in fostering high-level cognitive processing and analytical assessment as well as independent abilities to solve problem. AI chatbots and digital learning assistants have been developed to provide real-time support; their effectiveness depends on students' willingness to engage with them. Several studies have examined AI's role in education, emphasizing its potential to improve learning efficiency, provide real-time feedback, and foster SDL (Roca et al., 2024). But all students haven't same knowledge or adaptation ability. Some factors like Lack of ICT Self-Efficacy, Perceived Complexity of AI Tools, Low Motivation for SDL, Limited Understanding of AI's Educational Benefits are responsible. Students struggle to use AI chatbots. To solve this problem, research, build a framework to overcome the challenges and find out the factors that have direct relation to help students to use AI chatbots and analyse the factors effectiveness on AI driven App (Ayanwale & Ndlovu, 2024).

Extensive research has investigated the incorporation of AI-driven applications within STEM education, underscoring their potential to enhance problem-solving abilities and boost students' self-efficacy. Findings reveal that AI-based learning tools, including intelligent tutoring systems, chatbot-assisted instruction, and adaptive learning platforms, facilitate individualized learning environments that respond to the specific cognitive and academic needs of each student. These applications encourage real-time input, computerize appraisals, and back intelligently problem-solving exercises, in this manner making a difference understudies pick up certainty in tending to complex STEM concepts (Sun et al., 2025).

A crucial advantage of AI in STEM instruction is the capacity of advancing SDL. Ponders demonstrate that understudies who connected with AI-powered chatbots and computerized coaching frameworks show expanded autonomy, tirelessness, and inspiration to dive into STEM disciplines (Pellas, 2025). Furthermore, AI applications enhance cognitive skills by analysing students' learning behaviors, pinpointing areas of weakness, and offering tailored suggestions to boost problem-solving effectiveness.

RQ 1: What factors determine PEU of AI chatbots in STEM learning?

RQ 2: How does AI-powered learning increase students' problem-solving capabilities and SDL?

RQ 3: How does ICT self-efficacy influence students' adoption of AI-powered STEM education apps?

The key objective of the article is to investigate how AI-powered tools influence students' problem-solving skills and self-efficacy in STEM education. A major focus is to analyse how ICT Self-efficacy, Technology Acceptance and Learning Motivation (TA & LM), PEU, PC, and learning inspiration contribute to students' willingness to accept AI-powered tools (Tam et al., 2020). This study intends to create a thorough conceptual framework that combines theories of technology acceptance, self-efficacy, and motivation to improve AI-driven learning environments. By pursuing these goals, the research aims to connect the adoption of AI with successful learning results, thereby boosting students' confidence, engagement, as well as problem-solving abilities in STEM education. The study utilizes the SPLSS to explore the key determinants influencing the acceptance process and effectiveness of AI-enhanced learning environments (Al-Areeshi, 2025). It methodically examines the connections among ICT self-efficacy, PEU, PU, learning inspiration, and self-directed learning with technology (SDLT) to assess their influence on student engagement with AI-driven educational platforms (Mokmin, 2022). The research methodology includes a systematic data collection approach, employing surveys directed at STEM students to evaluate their experiences with AI chatbots and digital learning resources. The data gathered is analysed through SPLSS to determine how effectively AI-powered platforms facilitate students' independent learning, enhance their problem-solving abilities, and provide tailored feedback. This research is the inaugural effort to utilize the SPLSS model for examining AI adoption within STEM education. It offers a distinctive framework that integrates personal elements (ICT self-efficacy, SDLT) alongside TAM constructs (PU, PEU) to evaluate their influence on problem-solving and self-efficacy (Kong et al., 2025). The contribution of this paper is the factors that were used. In this research thirteen factors are used for AI chatbots independent variable. In the previous research seven factors are used as variables. The emphasis on cognitive outcomes, rather than only academic achievement, differentiates it from prior studies. IPMA enhances practical significance by prioritizing critical adoption factors. The use of SPLSS model in STEM education is new and for this the factors effectiveness becomes more understandable.

LITERATURE REVIEW

AI powered in STEM education app: scope and characteristics

Artificial Intelligence (AI) is revolutionizing STEM education by offering adaptive, personalized, and interactive learning experiences. Applications powered by AI deliver immediate feedback, automate assessments, and provide real-time assistance, allowing students to pursue self-directed learning and tackle problems effectively (Montejo et al., 2025). These tools encompass AI-driven chatbots, intelligent tutoring systems, and interactive simulation platforms, which facilitate a deeper understanding of complex STEM concepts through experiential learning. The role of AI in STEM education goes beyond merely delivering content. AI tools can analyze students' learning behaviours, pinpoint areas of difficulty, and provide customized recommendations, thereby ensuring a tailored educational experience. Additionally, these tools promote collaborative learning by incorporating peer discussions, AI-supported group projects, and virtual experiments that replicate real-world STEM scenarios. Moreover, AI improves accessibility by offering automated transcriptions, language translation, and adaptive learning environments that cater to students with varying learning needs (Hwang & Yi, 2025). Nevertheless, despite the many advantages of AI in STEM education, several challenges persist. A key concern is the need to align AI applications with established teaching methodologies to enhance their effectiveness in structured educational contexts. Furthermore, an over-dependence on AI tools could potentially hinder students' critical thinking and problem-solving abilities, highlighting the importance of balancing AI-driven learning with traditional educational methods. Ethical issues such as data privacy, algorithmic bias, and disparities in accessibility must also be addressed to ensure equitable and inclusive AI integration (Lee et al., 2022; Bergdahl & Sjöberg, 2025). In conclusion, AI-enhanced STEM education applications hold the promise of transforming learning by increasing engagement, offering personalized support, and nurturing independent problem-solving capabilities.

Previous studies and STEM education app enhancing problem-solving skills and self-efficacy

Extensive research has investigated the incorporation of AI-driven applications within STEM education, underscoring their potential to enhance problem-solving abilities and boost students' self-efficacy. Findings reveal that AI-based learning tools, including intelligent tutoring systems, chatbot-assisted instruction, and adaptive learning platforms, deliver personalized educational experiences tailored to the unique needs of each student. These applications facilitate real-time feedback, automate assessments, and support interactive problem-solving activities, thereby helping students gain confidence in addressing intricate STEM concepts (Rönkkö & Cho, 2022).

A significant advantage of AI in STEM education is its capacity to promote self-directed learning. Studies indicate that students who interact with AI-powered chatbots and automated tutoring systems exhibit increased independence, persistence, and motivation to delve into STEM disciplines (Hwang & Yi, 2025). Furthermore, AI applications enhance cognitive skills by analyzing students' learning behaviours, pinpointing areas of weakness, and offering tailored suggestions to boost problem-solving effectiveness. Nevertheless, challenges persist. Research indicates that students with low ICT self-efficacy may find it difficult to utilize AI-powered tools due to perceived complexity and a lack of confidence in their technological skills. Additionally, there is a pressing need for improved alignment between AI-driven learning models and conventional teaching methods, as an over-dependence on AI tools could impede the development of critical thinking and problem-solving skills if not effectively integrated into established educational frameworks. Ethical issues, including data privacy, algorithmic bias, and disparities in accessibility, have also been recognized as obstacles to the broader implementation of AI in education (Bayanova et al., 2023). In conclusion, earlier studies highlight the significant impact of AI-driven STEM education applications on improving problem-solving abilities and self-confidence. Nevertheless, to fully realize their potential, future research should aim to connect AI technology with effective teaching strategies, promote accessibility, and tackle ethical issues. By enhancing AI-integrated learning environments, educators can establish a more inclusive, engaging, and efficient framework that enables students to cultivate essential problem-solving skills and confidence in STEM fields (Rönkkö & Cho, 2022).

TOWARDS CONCEPTUAL MODEL AND HYPOTHESES

ICT self-efficacy, self-directed learning with technology, STEM education variable, technology acceptance and learning motivation, intention to use AI chatbots, perceived convenience, and enhanced performance expectation

These factors serve as essential indicators in assessing students’ engagement with technology enhanced learning, particularly in STEM education. Before adopting digital learning tools, students often form expectations based on their perceived ability to use technology effectively, their motivation for learning, and the compatibility of these tools with their educational needs. ICT self-efficacy plays a crucial role in this process, as students with higher confidence in their technological skills are more likely to explore and integrate digital resources into their learning routines. When students’ expectations regarding the usability and effectiveness of technology are met, they tend to persist in using it; however, unmet expectations can lead to reluctance or discontinuation of technology adoption (Esiyok et al., 2025). Satisfaction with digital learning tools can be categorized into immediate, task-specific satisfaction and long-term cumulative satisfaction. Task specific satisfaction arises from a positive experience with technology in a single learning instance, while cumulative satisfaction develops from repeated positive experiences, reinforcing long-term engagement (Relmasira et al., 2023).

Self-directed learning with technology is closely linked to students' willingness to adopt digital learning tools. Studies suggest that the ability to independently explore, experiment, and control one’s learning process positively impacts the adoption of educational technologies. The flexibility to experiment with different tools, modify approaches, and recover from mistakes builds students’ confidence and fosters continuous usage (Obiwuru, 2024). Observability also plays a key role, as students are more inclined to adopt technology when they see their peers successfully using it. Visible engagement with technology among classmates encourages discussions, knowledge sharing, and a collective sense of digital learning culture (Parsakia, 2023). Technology acceptance is a key determinant of students' willingness to incorporate digital tools into their learning process. According to the Technology Acceptance Model (TAM), students' perceptions of usefulness and ease of use significantly influence their adoption decisions (Ayanwale & Ndlovu, 2024). If students perceive technology as beneficial and easy to navigate, they are more likely to accept and integrate it into their studies. Moreover, observability plays a role in technology acceptance, as students are more inclined to adopt digital tools when they see their peers successfully utilizing them. Visible engagement within academic environments fosters discussions, collaboration, and a collective learning culture that encourages broader technology adoption (Yu, 2025).

Learning motivation also plays a crucial role in determining students’ engagement with digital learning tools. Motivation can be intrinsic, where students are driven by curiosity and personal interest in technology, or extrinsic, where external factors such as academic performance, institutional support, or peer influence encourage adoption (Lia, 2023). Research suggests that when students feel that technology supports their learning goals and enhances their educational experience, their motivation to engage with it increases. Perceived compatibility further influences motivation, as students are more likely to integrate technology when it aligns with their prior knowledge, study habits, and educational objectives (Roca, 2024). Perceived convenience plays a crucial role in AI chatbot adoption, as users prefer technologies that simplify tasks, reduce effort, and save time. Chatbots equipped with natural language processing (NLP) and machine learning capabilities enable users to receive instant responses, automate repetitive tasks, and access information seamlessly. The ability to interact with AI chatbots across multiple devices and platforms further enhances their perceived convenience, making them an attractive alternative to traditional customer service or information retrieval methods (Obiwuru, 2024).

Additionally, the visibility of AI chatbot effectiveness within peer or workplace environments influences adoption decisions, as users who observe successful interactions are more likely to develop positive perceptions and confidence in the technology. Upgraded execution desire is another deciding figure in chatbot selection. Users anticipate that AI chatbots will not only automate tasks but also improve overall efficiency and productivity. Research indicates that when AI-driven tools align with users’ goals such as improving learning outcomes, increasing workplace efficiency, or providing accurate recommendations, adoption rates increase (Roca et al., 2024; Sun et al., 2025). However, if users perceive chatbots as unreliable, prone to errors, or lacking personalization, their motivation to integrate them into their workflow decreases. Compatibility with users' existing digital habits and workflows further strengthens adoption, as individuals prefer technologies that seamlessly integrate into their routines rather than disrupt them. Accordingly, the following hypotheses are formed:

- Hypothesis 1 (H1): *ICT self-efficacy positively affects the perceived ease of use (PEU) of AI chatbots in education.*
- Hypothesis 2 (H2): *ICT self-efficacy positively affects the PU of AI chat bots in education.*
- Hypothesis 3 (H3): *Perceived ease of use (PEU) emphatically influences the perceived usefulness (PU) of AI chatbots in education.*

- Hypothesis 4 (H4): *Perceived usefulness (PU) emphatically influences the deliberate to utilize AI chatbots in education.*
- Hypothesis 5 (H5): *Perceived ease of use (PEU) emphatically influences the purposeful to utilize AI chatbots in education.*
- Hypothesis 6 (H6): *Self-directed learning with technology (SDLT) emphatically influences the purposeful to utilize AI chatbots in education.*
- Hypothesis 7 (H7): *Self-directed learning with technology (SDLT) emphatically influences the purposeful to utilize AI chatbots in education.*
- Hypothesis 8 (H8): *Deliberate to utilize AI chatbots emphatically influences the real utilize of AI chatbots in education.*

Personal innovativeness

Development hypothesis for the most part classifies clients of innovation as exceedingly imaginative people who are dynamic searchers of innovational thoughts. They are a particular sort of client who adapts with tall levels of vulnerability and creates positive eagerly towards acknowledgment. In this sense, individual innovativeness points to create positive convictions on innovational innovation. It is contended that the most elevated effect on people cognitive translations of data innovation relate to variables of individual innovativeness, which can be seen as an occurrence of risk-taking affinity that shows up as a result of utilizing modern innovation (Al-Areeshi, 2025).

This demonstrate is as a rule influenced by the vital and compelling fronts in this demonstrate, seen ease of utilize and seen value of innovation. The previous demonstrates the degree to which any client accepts that a particular innovation would improve their execution for specific purposes. The last mentioned concerns the degree to which a client accepts that employing a specific innovation diminishes exertion. These considers affirm a noteworthy relationship between behavioral purposeful and seen convenience and ease of utilization. In this way, the proposed conceptual demonstrate suggests that individual innovativeness features a critical effect on seen convenience and ease of utilize, which shape the essential pertinence for selection of metaverse frameworks (Hwang & Yi, 2025). Accordingly, the following hypotheses are formed:

- Hypothesis 9 (H9): *STEM instruction factors emphatically influence the seen convenience (PU) of AI chatbots in education.*
- Hypothesis 10 (H10): *STEM education variables positively affect the perceived ease of use (PEU) of AI chatbots in education.*
- Hypothesis 11 (H11): *Perceived convenience positively affects the intention to use AI chatbots in education.*
- Hypothesis 12 (H12): *Enhanced performance expectation positively affects the intention to use AI chatbots in* education.
- Hypothesis 13 (H13): *Technology acceptance and learning motivation positively affect self-directed learning with technology (SDLT).*

The conceptual framework

The current study proposed a conceptual framework that measures the adoption of AI powered in STEM Education App by examining three main attributes namely, Intention to use AI Chatbots, Self-directed learning with technology and Technology acceptance and learning motivation as coined with other independent variables of ICT self-efficacy, STEM education Variable, Perceived convenience, and Enhanced performance expectation, and Perceived Ease of Use, Perceived Usefulness. In other words, Actual AI Chatbot Usage is measured by ICT self-efficacy, Self-directed learning with technology, STEM education Variable, Technology acceptance and learning motivation, Intention to use AI chatbots, Perceived convenience, and Enhanced performance expectation as illustrated below.

METHODS

Data collection

Within the scope of this study a Google form is used to gather data over two weeks, from February 21 to February 7 March, 2025 and the participants could attend anytime during this time frame at their convenience. The first section of the survey was dedicated to gather demographic data like gender, profession, age, educational qualifications, field of study, technology proficiency level etc (Roca et al., 2024). These questions were designed to understand the diverse backgrounds of the participants, which is crucial to conduct the survey. The second section is main part of the survey where the participants were asked about ICT Self-efficacy, Actual AI Chatbot Usage (AACU), Intention to Use AI Chatbots (IUAC), Technology Acceptance & Learning Motivation and so on. These questions were designed using revalidated scales and the validity of the content was verified following the appropriate verification methods. Five-point Likert scales were employed to enhance the reliability of the measurements in the final section, the participants were asked about benefits, challenges of using AI chatbots. It also asked how STEM background influence perception of AI chatbots, how AI chatbots improve better support in STEM learning. Though this part is optional but from this part we can understand the relation of participants with AI chatbots.

Students often turn to their instructors for help when they encounter obstacles in using technological tools, as teachers typically have more advanced skills and experience with such technologies. In this study, SEM was applied to examine the article hypotheses, with the sample size deemed sufficient for reliable analysis (Lee et al., 2022). Although the hypotheses were originally derived from recognized theoretical models, they were modified where appropriate to suit the specific context of the Internet of Things (IoT). The data analysis was conducted using SmartPLS (version 4.1.1.1) for SEM, along with SPSS to support the structural model assessment.

Personal/demographic information

Table 1 provides detailed information on the demographic composition of the respondents. Where among the 117 respondents (Male = 25 (21.4%)) and (Female = 92 (78.6%)). The majority of participants, 72.7% (85) were between 21- 25 years old, followed by 7.7% (9) were between 26-30 years old, indicating that the sample predominantly consisted of young men. Additionally, 82.9% (97) held a Bachelor's degree, while 15.4% (18) had a Master's degree, illustrating that the response pool is highly educated. This demographic profile highlights the importance of targeting young, educated individuals who actively use AI chatbots to enhance their self-efficacy as well as problem-solving abilities.

Table 1

Demographic data of the participants.

Criteria	Factor	Frequency	Percentage
Gender	Male	25	21.40%
	Female	92	78.60%
Age (In Years)	Between 16 and 20	19	16.20%
	Between 21 and 25	85	72.70%
	Between 26 and 30	9	7.70%
	Between 31 and 35	2	1.70%
	Above 35	2	1.70%
Education Level	Undergraduate	97	82.9%
	Master's	18	15.4%
	PhD	0	0%
	MBBS	2	1.70%

Study instrument

A survey comprising 33 items was developed as the primary research instrument this survey was designed to assess 10 distinct constructs outlined in the questionnaire with their respective sources detailed in **Table 2** (**see appendix**) items from prior studies were adapted and customized to better align with the objectives of this research ensuring the findings would be more relevant and applicable.

Pilot study of questionnaire

Table 3 displays the CA values evaluated for the measurement scales. This study carried out an initial performance evaluation of the dependability of the questionnaire items. A random selection of participants for the pilot study was taken from a group of 117 students. Considering that the total participant is 117, employing a sample size of 10% (in accordance with research guidelines) leads to 11.7; hence, a total of 12 students took part in the pilot study. In the next stage of the pilot study, SPSS software was used to conduct a Cronbach's alpha (CA) test to measure the internal consistency of the items. The findings indicated a reliability coefficient of 0.70, which is regarded as acceptable since this research is situated in the realm of Science (Roca et al., 2024).

Table 3

CA Values for Pilot Study (CA ≥0.70).

Items	CA
Actual AI Chatbot Usage	0.943
EPE	0.901
ICT Self-Efficacy	0.843
Intention to Use AI Chatbots	0.933
PC	0.917
PEU	0.893
PU	0.910
SDLT	0.939
TA & LM	0.908
TB STEM Education	0.890

Common method bias

The assessment of common method bias was conducted using Variance Inflation Factor (VIF) values from the inner model. In the research, all VIF values remained under 3.33. Therefore, we can conclude that the model is not affected by common method bias (Montejo et al., 2025). **Table 4** demonstrates that all values are below 3.33, allowing us to affirm that this model is free from common method bias.

Survey structure

The survey questionnaire that was distributed to the students participating in the study consists of three main parts:

- The first part has questions about the personal information of the responders.
- The second part featured 33 items concerning ICT self-efficacy, SDLT, STEM education variables, TA & LM, IUAC, PC, enhanced performance expectations (EPE).
- The third part was optional and solicited responses to questions regarding the usefulness of AI chatbots.

Upon completion of the questionnaires, the 33 items were evaluated using a five-point Likert Scale, with responses of strongly disagree (1) to strongly agree (5) range.

Table 4
Variance Inflation Factor Analysis.

	VIF
EPE -> Intention to Use AI Chatbots	3.223
ICT Self-Efficacy -> PEU	2.544
ICT Self-Efficacy -> PU	2.136
Intention to Use AI Chatbots -> Actual AI Chatbot Usage	3.387
PC -> Intention to Use AI Chatbots	3.244
PEU -> Intention to Use AI Chatbots	2.638
PEU -> PU	1.176
PU -> Intention to Use AI Chatbots	1.648
SDLT -> Actual AI Chatbot Usage	3.387
SDLT -> Intention to Use AI Chatbots	2.346
TA & LM -> SDLT	1.000
TB STEM Education -> PEU	2.544
TB STEM Education -> PU	2.921

RESULT

Data analysis

The SPLSS model is used to examine the relationships among theoretical design factors and validate article hypotheses. SPLSS is implemented using an advanced statistical framework to analyze the proposed research model (Bergdahl & Sjöberg, 2025). SPLSS is particularly suitable for predictive analytics in theoretical models that require deep latent variable estimation (Montejo et al., 2025). The application of SPLSS in this study follows standardized guidelines for research studies in computational social sciences (Pellas, 2025). Consequently, the research model is analyzed in a systematic two-step approach (involving the assessment of measurement as well as structural models) as emphasized by the methodological recommendations of Brown (1995). Moreover, PLS-SEM analysis is supported, assessed, and validated by applying ANN with IPMA. ANN surveys the subordinate and autonomous factors, and it works best for exploring non-linear or complex connections among input and yield develops. It serves as a work estimation instrument.

SPLSS introduces a novel methodological approach: Semantic Predictive Importance Analysis (SPIA). The primary objective of SPIA is to evaluate research model constructs by assessing their semantic relevance and predictive performance. Additionally, SPLSS enhances structural model evaluation by integrating latent construct estimations, thus improving the interpretability and predictive accuracy of theoretical frameworks. The SPLSS model incorporates key statistical mechanisms such as factor decomposition, latent trajectory modeling, and covariance-based structural relationships, enabling a robust estimation of theoretical constructs (Rönkkö & Cho, 2022). The methodological advancements in SPLSS provide a structured analytical foundation for research studies requiring multidimensional predictive modeling. The predictive performance of SPLSS is further validated using a cross-validation framework to ensure model reliability and consistency. In summary, SPLSS has been used in the research framework as a structured predictive modeling technique to enhance hypothesis testing and theoretical validation. In short, MLP neural network has been applied to the research model as an ANN technique for its training and testing.

Convergent validity

Effective techniques for calculating or analyzing the measurement model include the examination of construct reliability, which includes composite reliability (CR), Dijkstra-Henseler's rho (pA), and CA, as well as validity measures (both convergent and discriminant). **Table 4** shows that the CA values for CR are over the 0.7 minimum requirement, ranging from 0.843 to 0.9. Also, **Table 5** presents CR values of 0.857 to 0.944, which also surpasses required threshold of 0.7. As a complementary approach, researchers should apply Dijkstra-Henseler's rho reliability coefficient (ϱA) to calculate construct reliability. Similar to CA and CR, the reliability coefficient should be 0.70 or higher in exploratory studies, with values exceeding 0.8 or 0.9 recommended for more advanced research stages. The table clearly shows that the reliability coefficient exceeds 0.70 for all individual measurement constructs, reinforcing the notion of construct reliability. Ultimately, it can be concluded that the constructs or items are assumed to be free from significant errors in an acceptable manner. To assess convergent validity, average variance extracted (AVE) and factor loading tests are performed. As illustrated in the table, each factor loading value is found to be above the suggested benchmark of 0.7. Furthermore, **Table 5** (see appendix illustrates that the calculated AVE scores all exceed the standard cutoff of 0.5, spanning from 0.680 to 0.898. Taking these results into account, all constructs demonstrate evidence of convergent validity.

Table 5

Acceptable Results for Convergent Validity Include Factor Loading, CA, and CR ≥0.70 & AVE >0.5.

Construct	Item	Factor Loading	CA	CR (rho_a)	pA	AVE
Actual AI Chatbot Usage	AACU1	0.939	0.943	0.944	0.963	0.898
	AACU2	0.955				
	AACU3	0.949				
EPE	EPE1	0.898	0.901	0.906	0.938	0.834
	EPE2	0.926				
	EPE3	0.916				
ICT Self-Efficacy	ICT SE1	0.748	0.843	0.857	0.895	0.680
	ICT SE2	0.828				
	ICT SE3	0.873				
	ICT SE4	0.845				
Intention to Use AI Chatbots	IUAC1	0.939	0.933	0.935	0.957	0.882
	IUAC2	0.951				
	IUAC3	0.926				
PC	PC1	0.908	0.917	0.918	0.948	0.858
	PC2	0.935				
	PC3	0.914				
PEU	PEU1	0.935	0.893	0.894	0.933	0.824
	PEU2	0.895				
	PEU3	0.892				
PU	PU1	0.896	0.910	0.911	0.943	0.847
	PU2	0.920				
	PU3	0.945				
SDLT	SDLT1	0.928	0.939	0.941	0.956	0.846
	SDLT2	0.907				
	SDLT3	0.906				
	SDLT4	0.937				
TA & LM	TA & LM1	0.908	0.908	0.908	0.942	0.845
	TA & LM2	0.935				
	TA & LM3	0.914				
TB STEM Education	TBSE1	0.877	0.890	0.897	0.924	0.751
	TBSE2	0.842				
	TBSE3	0.864				
	TBSE4	0.883				

Discriminant validity

To assess discriminant legitimacy, both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT) were evaluated. The results shown in **Table 5** (see appendix support the Fornell-Larcker criterion as stated in **Table 6** by showing that the values of AVEs and their square roots are greater than the correlations with other variables. **Table 7** outlines the outcomes of HTMT ratio. As indicated, every construct exhibited a value under the recognized threshold of 0.85, suggesting consent with the HTMT ratio (Bayanova et al., 2023). According to these results, discriminant legitimacy is affirmed. The analysis results for the measurement model showed no issues related to validity or reliability. Therefore, the data gathered can be applied to examine and validate the components of the structural framework.

Table 6

Fornell-Larcker Scale.

	Actual AI Chatbot Usage	EPE	ICT Self-Efficacy	Intention to Use AI Chatbots	PC	PEU	PU	SDLT	TA & LM	TB STEM Education
Actual AI Chatbot Usage	0.948									
EPE	0.835	0.913								
ICT Self-Efficacy	0.820	0.774	0.825							
Intention to Use AI Chatbots	0.885	0.890	0.823	0.939						
PC	0.853	0.865	0.809	0.846	0.927					
PEU	0.825	0.796	0.820	0.812	0.861	0.908				
PU	0.816	0.804	0.825	0.869	0.843	0.855	0.921			
SDLT	0.881	0.831	0.788	0.839	0.826	0.826	0.769	0.920		
TA & LM	0.862	0.842	0.856	0.878	0.868	0.838	0.856	0.827	0.919	
TB STEM Education	0.788	0.808	0.779	0.760	0.765	0.781	0.743	0.821	0.781	0.867

Model fit

In this research, SmartPLS employs a range of model fit indicators, including exact fit statistics, the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), RMS_theta, geodesic distance (d_G), squared Euclidean distance (d_ULS), and the Chi-square (Chi2) statistic, to evaluate how well the PLS-SEM model aligns with the data. As presented in **Table 8**, SRMR is particularly useful for measuring the discrepancy between the actual correlation matrix and the one predicted by the model. An SRMR value below 0.08 generally suggests an acceptable model fit. Similarly, the NFI, which assesses model fit by comparing the Chi2 value of the estimated model to that of a baseline (null) model, should typically exceed 0.90 to indicate good fit. Nonetheless, NFI may not consistently reflect model fitness effectively, as it can vary with the number of parameters involved. The relevance of d_ULS and d_G is significant because these fit evaluations reveal the discrepancies between empirical covariance matrix and the matrix obtained from the composite factor design.

Table 7

Heterotrait-Monotrait Ratio.

	Actual AI Chatbot Usage	EPE	ICT Self-Efficacy	Intention to Use AI Chatbots	PC	PEU	PU	SDLT	TA & LM	TB STEM Education
Actual AI Chatbot Usage										
EPE	0.302									
ICT Self-Efficacy	0.510	0.575								
Intention to Use AI Chatbots	0.641	0.367	0.922							
PC	0.417	0.051	0.610	0.513						
PEU	0.798	0.587	0.470	0.689	0.352					
PU	0.800	0.850	0.634	0.542	0.423	0.449				
SDLT	0.734	0.502	0.481	0.695	0.289	0.501	0.430			
TA & LM	0.132	0.628	0.672	0.753	0.350	0.729	0.242	0.393		
TB STEM Education	0.655	0.301	0.771	0.430	0.439	0.769	0.219	0.594	0.763	

Table 8

Model Fit Indicators.

	Complete	
	Saturated model	Estimated model
SRMR	0.051	0.087
d_ULS	1.438	4.220
d_G	2.280	2.652
Chi-square	1324.728	1398.860
NFI	0.755	0.741

Hypotheses Testing Using PLS-SEM

To evaluate the interconnections among the various theoretical constructs in the structural model, the structural equation design was applied using Smart PLS and maximum likelihood estimation. The suggested hypotheses were assessed utilizing these analytical tools. The model demonstrated significant predictive capability, with variance percentages of 68% for SDLT, 75% for PEU, 76% for PU, 84% for AACU, and 86% for Users' IUAC. These findings are presented in **Table 9** along with **Figure 1** and **2**. The estimations and results were achieved through the PLS-SEM technique, facilitating the confirmation of hypotheses (Relmasira et al., 2023). The beta (β) values, t-values, and p-values associated with these hypotheses are listed in **Table 10**. All researchers unequivocally supported these hypotheses. The data analysis indicates that empirical findings corroborate hypotheses H1 through H13. The correlations between ICT Self-efficacy and PEU (β = 0.617, P (PU) (β = 0.403, P < 0.001), PEU (β = 0.058, P < 0.001), SDLT (β = 0.218, P < 0.001), and IUAC (β = 0.491, P < 0.001) endorse hypotheses H1 through H7.

The hypothesis testing results reveal varying strengths in the relationships between the variables shown in **Figure 2**. The strongest relationship was found between Technological Acceptance (TA) and Learning Motivation (LM) on SDLT (H13), with a high t-value of 15.446. Additionally, ICT self-efficacy strongly influenced PEU (H1) with a t-value of 7.040, suggesting that confident ICT users perceive technology as easier to use. SDL also positively impacted Actual AI Chatbot Usage (AACU) (H7), with a t-value of 2.793. Moderate relationships were observed between External Perceived Ease (EPE) and Intention to IUAC (H12), with a t-value of 3.174, and between IUAC and AACU (H8), with a t-value of 3.065. PU positively influenced IUAC (H4), with a t-value of 2.979 that showed in **Table 10**.

Table 9

R^2 of the Endogenous Latent Variables.

	R-square	Results
Actual AI Chatbot Usage	0.845	Substantial
Intention to Use AI Chatbots	0.865	Substantial
PEU	0.756	Substantial
PU	0.763	Substantial
SDLT	0.681	Substantial

Table 10

*Hypotheses-evaluation of study framework (significant at p** <=0.01, p*<0.05).*

Hypothesis	Relationships	Path	T statistics (|O/STDEV|)	P-value	Direction	Decision
H1	ICT SE -> PEU	0.617	7.040	0.000	Positive	Validated
H2	ICT SE -> PU	0.312	1.967	0.049	Positive	Validated
H3	PEU -> PU	0.510	4.140	0.000	Positive	Validated
H4	PU -> IUAC	0.403	2.979	0.003	Positive	Validated
H5	PEU -> IUAC	0.058	0.522	0.002	Positive	Validated
H6	SDLT -> IUAC	0.218	1.618	0.005	Positive	Validated
H7	SDLT -> AACU	0.468	2.793	0.005	Positive	Validated
H8	IUAC -> AACU	0.491	3.065	0.002	Positive	Validated
H9	TBSE -> PU	0.102	1.120	0.026	Positive	Validated
H10	TBSE -> PEU	0.300	3.201	0.001	Positive	Validated
H11	PC -> IUAC	0.012	0.084	0.033	Positive	Validated
H12	EPE -> IUAC	0.420	3.174	0.002	Positive	Validated
H13	TA & LM -> SDLT	0.827	15.446	0.000	Positive	Validated

Figure 1
Research model.

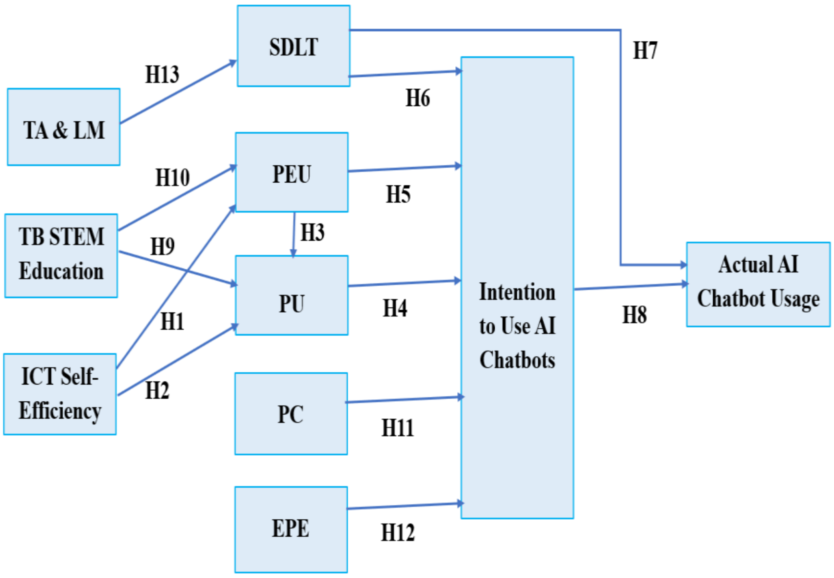
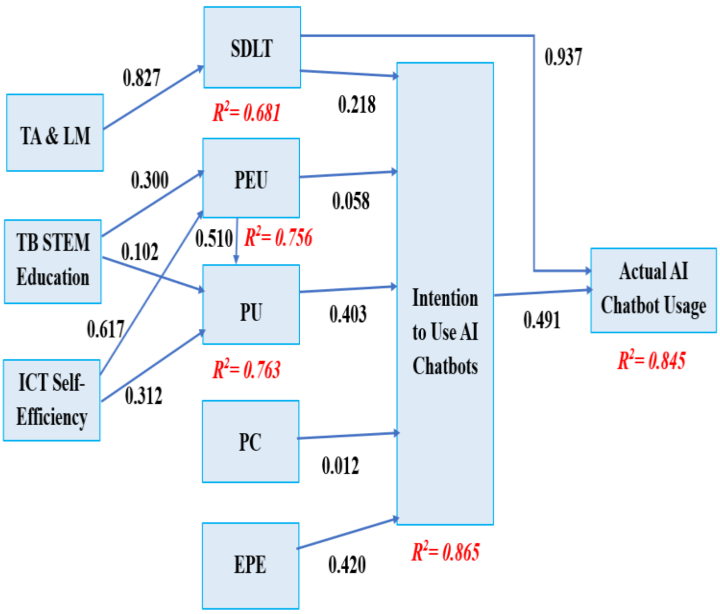


Figure 2
*Path coefficient of the model (significant at p** <=0.01, p*<0.05).*



ANN results

The research involves the use of SPSS to conduct ANN analysis (Pellas, 2025), using only the predictors obtained from PLS-SEM i.e., the analysis only accounts for factors of PEU, PC, SDLT, AACU, EPE, ICTSE, and TA&LM. The structure of the ANN model is given in **Figure 3–6**; a single output neuron (users' intention to use AI Chatbots), along with multiple input neurons (PEU, PU, PC, EPE, SDLT) constitute the ANN model. To facilitate deep-learning in every node of the output neuron, a deep ANN structure with two-hidden layers was used in this study (Tam et al., 2020). The sigmoid function was also applied to hidden and output neurons as an activation function. Furthermore, the investigation was made more capable in terms of execution by institutionalizing the input and yield neurons within the range [0, 1]. The training and testing data were taken in the ratio 90:10 while applying the ten-fold cross-validation technique to prevent ANN models from over-fitting. The root mean square of error (RMSE) is assessed to decide the accuracy of the neural network model. The RMSEs evaluated for training data was 0.1256 and for testing data was 0.1523. The ANN enhanced the accuracy of proposed research model as is evident from the insignificant disparity between values of SD (standard deviation) and RMSE evaluated for training data (equalling to 0.0081) and testing data (equalling to 0.0094). Here, the bias nodes appear disconnected from some parts of the network, particularly the output layer. The absence of explicit connections from the bias nodes does not mean they are unused or non-functional rather; it is a common simplification in neural network visualizations that is also present here.

A neural network model that predicts AI chatbot usage based on four input factors—Perceived Utility (PU), Perceived Ease of Use (PEU), Perceived Compatibility (PC), and Training-Based STEM Education—is depicted in the diagram. Three neurons in the hidden layer use the hyperbolic tangent activation function, which produces values in the range of -1 and 1. The output layer directly predicts chatbot usage using an identity activation mechanism.

Figure 3

ANN model

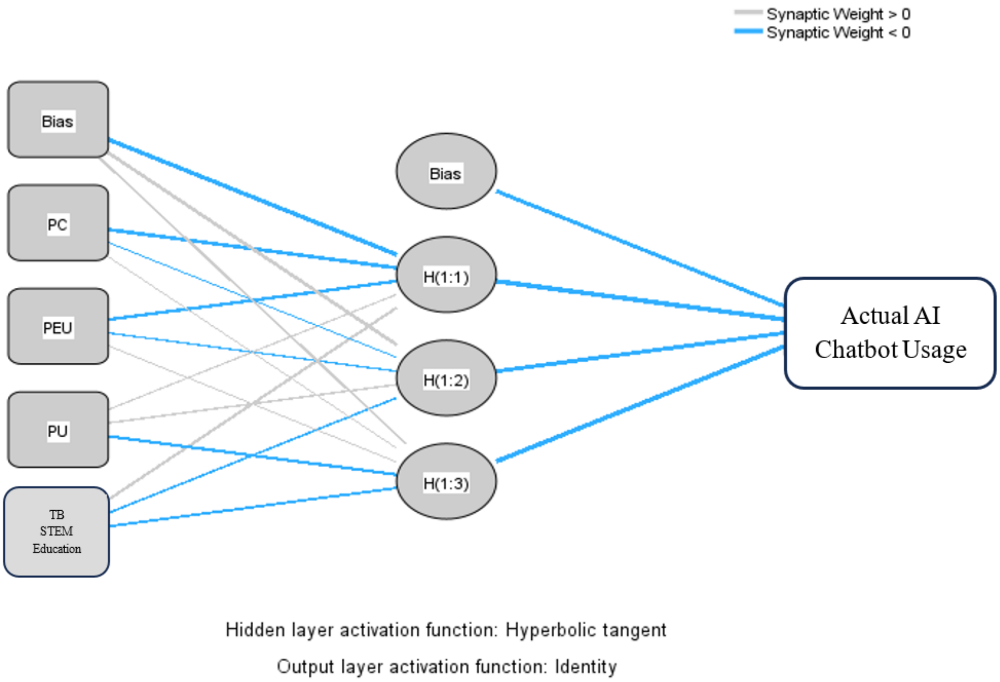


Figure 4

ANN model.

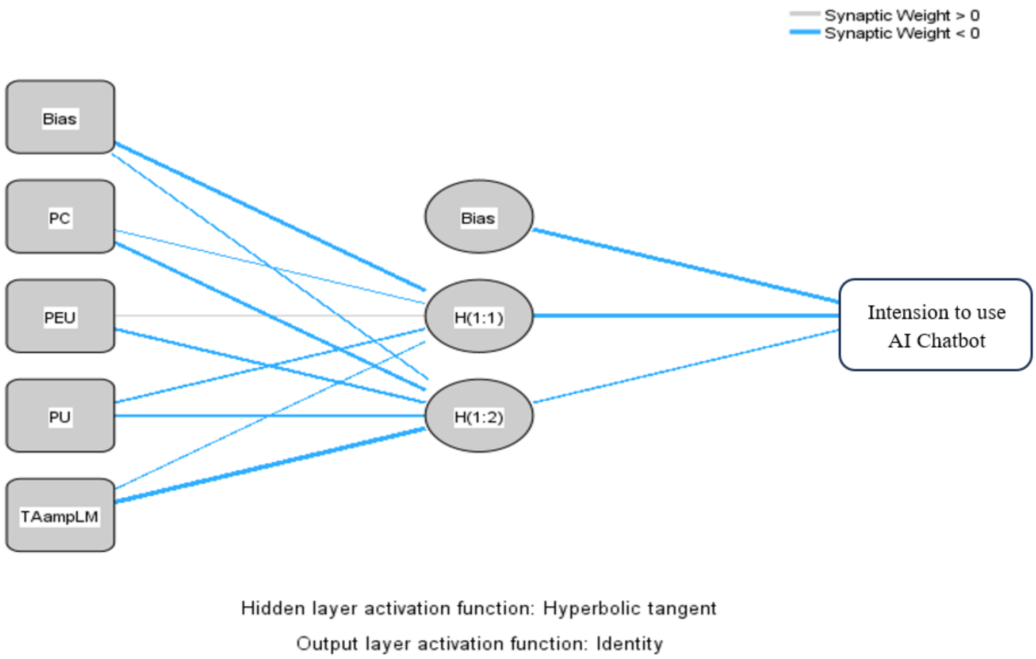


Figure 5
ANN model.

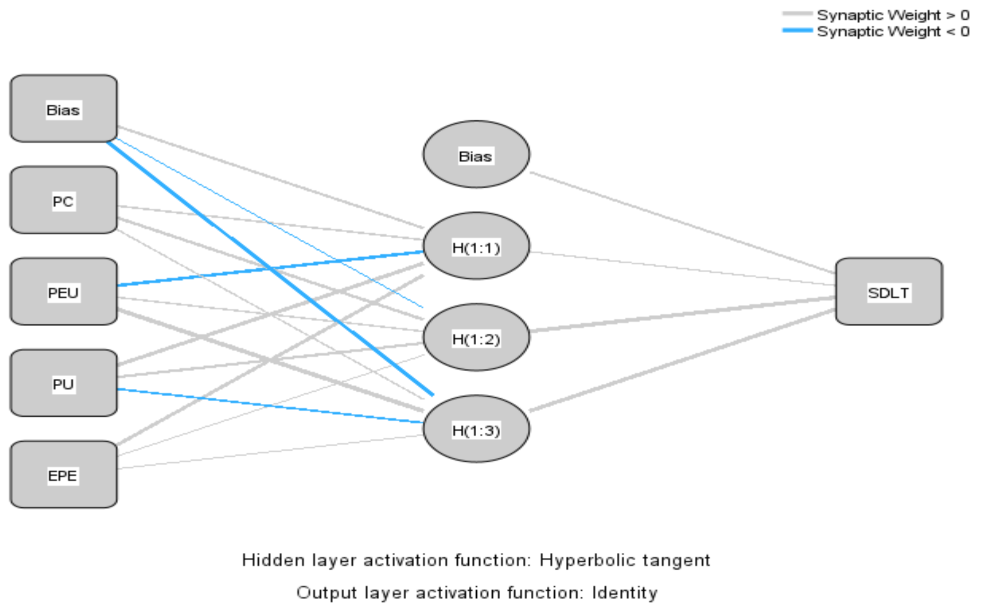
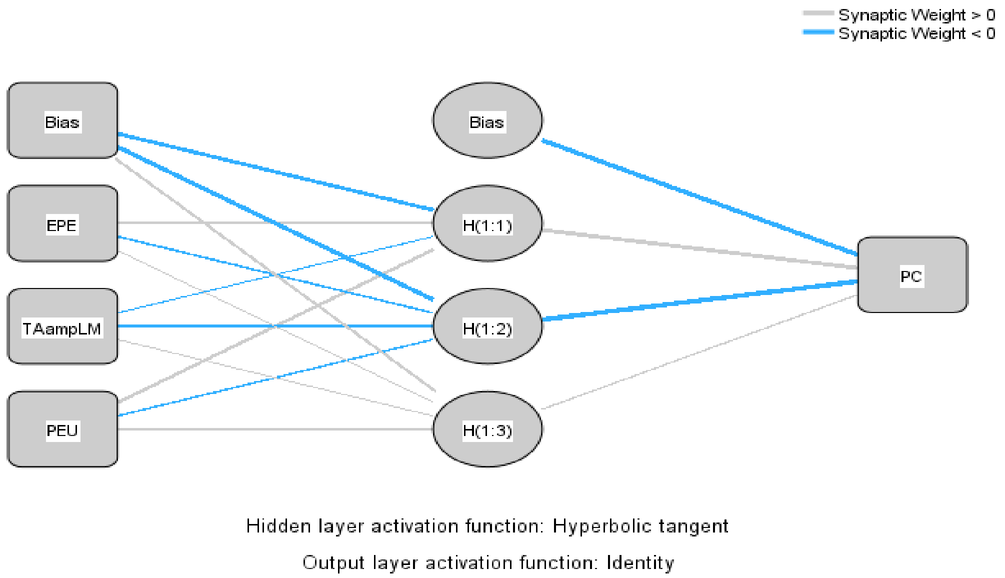


Figure 6
ANN model.



The neural network model predicts the deliberate to utilize AI chatbots based on four inputs: Perceived Compatibility (PC), Perceived Ease of Utilize (PEU), Perceived Usefulness (PU), and Preparing and Intensification of Dialect Models (TAampLM). The covered up layer comprises of two neurons employing a hyperbolic digression actuation work to capture nonlinear designs. The neural organize show predicts PC based on three inputs: Expected Performance Enhancement (EPE), Preparing and Intensification of Dialect Models (TAampLM), and PEU.

This diagram illustrates a feedforward neural network with three input features (EPE, TAampLM, and PEU), a bias node, and a hidden layer of three neurons using the hyperbolic tangent activation function. The output layer produces a single result labeled "PC" using an identity activation function, suitable for regression tasks. Connection lines show synaptic weights, where gray indicates positive weights and blue indicates negative weights.

Sensitivity analysis

Normalised importance is evaluated for each predictor by obtaining the ratio between its average importance value and maximum mean value of importance, and is represented in percentage form (Kong et al., 2025). Each indicator included in ANN demonstrating was assessed for cruel significance esteem and standardized significance esteem. The resultant values were recorded in **Table 11**. Further, the sensitivity analysis outcomes stated in **Table 11** suggest the order of significance of the three factors from among EPE, PC, PEU, PU, SDLT, TAampLM TBSTEMEducation, ICTSelfEfficacy, IntentiontoUseAIChatbots, Accordingly, IntentiontoU-seAIChatbots leads to other factors. Another fit degree named goodness-of-fit is utilized to assess the ANN application and strengthen its exactness and execution, which is as of now approved by other fit measures. Goodness-of-fit measure renders the same function in ANN application as R^2 in PLS-SEM analysis. However, ANN analysis offers better explanation of endogenous constructs, as it is attributed with greater predictive power (R compared to PLS-SEM (R^2 = 86.5%). Furthermore, since deep-learning ANN procedure superior clarifies the non-linear connections between demonstrate builds, there's some dissimilarity within the values of changes.

Table 11

Independent variable importance.

Independent Variable Importance		
	Importance	Normalized Importance
EPE	.056	19.5%
ICTSelfEfficacy	.073	25.5%
IntentiontoUseAIChatbots	.287	100.0%
PC	.158	55.1%
PEU	.054	18.7%
PU	.023	8.0%
SDLT	.213	74.1%
TAampLM	.070	24.2%
TBSTEMEducation	.066	22.8%

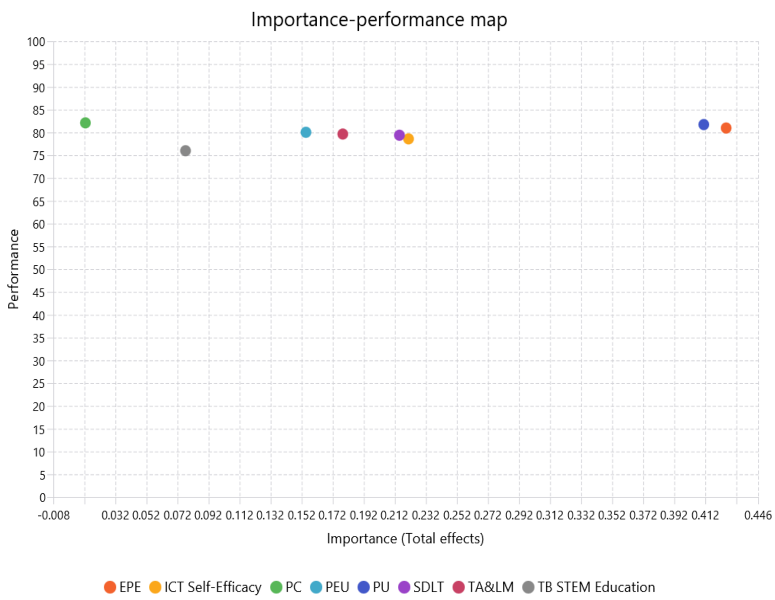
Importance-performance map analysis

Figure 7 represents the IPMA analysis. In this research, the IPMA technique was used within the PLS-SEM framework, with behavioural purpose selected as the outcome variable. IPMA enhances the interpretation of structural model results by incorporating both the relevance (importance) and effectiveness (performance) of latent variables.

As highlighted by Ringle and Sarstedt (2016), this approach goes beyond merely assessing path coefficients; it also evaluates the average performance levels of constructs and their associated indicators. The fundamental idea behind IPMA is to identify which variables have the strongest influence on the target variable and how well those variables are performing. In this study, ten constructs were examined: EPE, ICT self-efficacy, PC, PU, PEU, SDLT, TA, LM, and TB STEM education, all in relation to the aim to engage AI chatbots. Among these, PC demonstrated the highest performance, while TB STEM education scored lowest in performance but ranked third in terms of importance (Parsakia, 2023). Notably, ICT self-efficacy was found to have the least impact on behavioural intention.

Figure 7

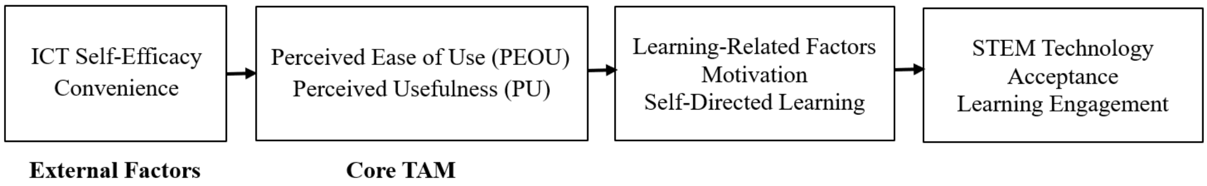
IPMA results



A concise conceptual framework diagram

Figure 8 represents perceived usefulness and perceived ease of use are treated as core TAM variables, while convenience and ICT self-efficacy are conceptualized as external factors influencing users' perceptions and behavioral intentions. Motivation and self-directed learning are incorporated as mediating learning-related constructs that explain how technology acceptance translates into meaningful learning engagement.

Figure 8
Concise conceptual framework.



DISCUSSION

In this research, we used Smart PLS 4 to perform Partial Least Squares (PLS) analysis and IBM SPSS for ANN analysis. Our methodology included evaluating reliability and validity, in addition to analyzing the path coefficients to assess the strength of the framework design. We aimed to investigate the relations among various concepts, such as ICT self-efficacy, Technology-Based STEM Education (TBSE), PEU, PU, EPE, IUAC (INT), Actual AI Chatbot Usage (ACT), and SDLT.

We opted for PLS for SEM in this investigation due to its capability to manage complex models and simultaneously measure multiple items, which is crucial for comprehending causal relationships among variables. Furthermore, PLS is particularly effective for assessing intricate predictive models that involve a range of research constructs and variables, making it a suitable choice for our study as also demonstrated by Sultan et al. (2025).

The current research explored the integration of AI-driven applications within STEM education and their impact on problem-solving abilities and self-efficacy, utilizing the SPLSS model. The results reveal that students' views on AI-integrated STEM applications are strongly shaped by their PEU, PU, as well as their personal sense of self-efficacy. These elements are vital in shaping students' readiness to adopt AI-based learning tools, aligning with previous research on technology acceptance in educational contexts. Specifically, students who view AI applications as easy to use and beneficial for their academic progress exhibit increased confidence in their problem-solving capabilities, which subsequently encourages higher adoption and continued usage.

The study's findings highlight the important effect of PEU in guiding students' attitudes toward technology acceptance. The robust correlation between self-efficacy and PEU suggests that students are more inclined to interact with AI-powered applications when the user interface is intuitive and requires minimal effort to navigate, a pattern similiarly which found by Işıklı and Fazlıoğlu (2026).

This result corroborates the idea that students prefer educational tools that are user-friendly and can be seamlessly integrated into their academic work. Additionally, the research shows that PU positively influences students' intentions to engage with technology, suggesting that when students recognize the tangible benefits of AI in enhancing their STEM learning experiences, their likelihood of adopting such technologies increases.

The outcomes of the research offer strong confirmation for the idea that AI-based tools in STEM education significantly contribute to boosting students' problem-solving skills and self-esteem. Future study should investigate the impact of extra factors, like gamification, interactive simulations, and AI-facilitated collaborative learning environments, on enhancing outcomes in STEM education. Moreover, long-term studies could be conducted to assess the lasting effects of AI-driven educational programs on students' academic performance and readiness for careers in STEM fields.

Theoretical and practical implications

This research builds upon earlier empirical studies by implementing the SPLSS model instead of relying exclusively on traditional statistical methods. The study adopts a novel hybrid analytical approach, thereby enhancing its contribution to the body of literature on AI-enhanced STEM education. Furthermore, the SPLSS model exhibits greater predictive accuracy than conventional SEM-based models, largely due to its advanced ability to detect intricate, non-linear interactions among the elements of the theoretical framework. By utilizing latent semantic structures, SPLSS provides deeper understanding into how problem-solving abilities are connected to individuals' sense of self-efficacy, establishing a more holistic model for grasping the role of AI-powered learning within STEM education. Besides, ANN demonstrate is credited with more prominent prescient control in comparison to PLS-SEM show basically due to the extra preferences advertised by profound ANN design in distinguishing of non-linear affiliation of hypothetical demonstrate components.

Managerial implications

The study presents key managerial implications for enhancing AI-powered STEM education tools. Developers should focus on user-friendly designs and clearly communicate academic benefits to boost adoption. Institutions must improve students' ICT self-efficacy through targeted training and promote SDL by integrating AI tools into learning platforms. Motivation and perceived performance gains should be emphasized via personalized feedback and gamified features (Pellas, 2025) Tailoring tools specifically for STEM content is essential, as revealed by IPMA analysis. Lastly, using predictive models like SPLSS and fostering cross-functional collaboration can guide effective, data-driven decision-making and product development.

Constraints of the current research and directions for upcoming investigations

This study is subject to a number of constraints. Firstly, the conceptual framework is constrained by its emphasis on a narrow range of variables, mainly problem-solving abilities and self-efficacy, without accounting for other psychological or environmental elements that could affect students' engagement with AI-enhanced STEM applications. Secondly, the analysis utilizes the SPLSS model, which, although useful, may not fully encompass the complexities of students' interactions with AI-based learning tools. Thirdly, data collection was carried out via online surveys, which could introduce sample bias, as students who are more knowledgeable or interested in AI technologies might have been more inclined to participate. Fourthly, while AI-powered applications can be applied in various educational contexts beyond STEM, this study is specifically centered on STEM education, which restricts its applicability to other disciplines. In addition, this article employed a convenience sample drawn from a single institutional context, which may limit the representativeness of the findings and the potential for response bias inherent in self-reported survey data, despite the use of validated measurement scales and statistical checks for common method bias. The cross-sectional design and reliance on perceptual measures are recognized as constraints on causal inference. Future research should investigate a wider array of influencing factors, including motivation, cognitive load, and long-term learning outcomes, and should also consider experimental or longitudinal methods to assess the lasting effects of AI-driven learning tools on students' academic success and self-efficacy (Lai, 2023). Besides, it can be overcome the limitations by employing multi-site and probability-based sampling across diverse institutions to improve representativeness and generalizability. To reduce response bias, studies should combine self-reported surveys with objective measures such as system log data, learning analytics, or observational methods. Longitudinal or experimental designs would allow stronger causal inferences and capture changes in students' perceptions and behaviors over time. Finally, validating the proposed model across different disciplines, educational levels, and cultural contexts would enhance the robustness and transferability of the findings.

CONCLUSION

This research establishes a comprehensive framework for comprehending how AI-driven applications in STEM education can improve students' problem-solving skills and bolster their confidence. By examining the relationships among ICT self-efficacy, user-friendliness, PU, and motivation to learn, the study emphasizes the significance of AI chatbots in creating a more involving and active learning experience. The findings reveal that these chatbots not only facilitate interactive learning but also motivate students to actively steer their own educational journeys. The ponder affirmed that students' self-efficacy in ICT is pivotal in forming their sees on AI chatbots, with user-friendliness and PU being basic components for innovation acknowledgment. The results demonstrated that AI contributes to increased engagement, enhanced problem-solving capabilities, and greater confidence in learning. SEM analysis reinforced the notion that AI-based tools can significantly improve STEM education, provided they are implemented in conjunction with traditional teaching methods for optimal results. The research underscores the necessity of further refining AI-driven educational tools to ensure they are user-friendly, effective, and inclusive for learners from various backgrounds. By leveraging AI chatbots, students can receive immediate support, personalized learning experiences, and an interactive setting that fosters improved problem-solving and deeper engagement. Looking ahead, it is vital to investigate the enduring affect over time, versatility, and integration of rising advances to progress AI-based instruction and maximize its benefits for understudies around the world. It can too outline how understudies see the innovational innovation utilized in instruction.

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Ethical statement

This study received ethics exemption from the relevant institutional research ethics committee, consistent with institutional guidelines for qualitative research involving voluntary adult participants in non-sensitive educational contexts. Written informed consent was obtained from all participants prior to data collection. Participants were fully informed of the study's objectives, data handling procedures, and their right to withdraw at any time without consequence. All data were anonymized, and participants are represented in the findings without personal or institutional identifiers.

Competing interests

The authors declare no competing interests.

Author contributions

All authors contributed equally to the conceptualization, methodology, data collection, formal analysis, interpretation of findings, preparation of the original manuscript draft, and revision and editing of the final version of the manuscript.

Data availability

The subjective information related to this is not freely open to guarantee the privacy and protection of the members. Be that as it may, extra data may be gotten from the comparing creator upon sensible ask and in understanding with moral rules.

AI disclosure

AI apparatuses were utilized as it was to support language refinement, organization, and drafting help amid composition arrangement. All conceptual advancement, interpretation, argumentation, and last publication obligation remained with the authors.

Biographical sketch

Morshada khanam Mim is a researcher affiliated with MSc, Department of Computer Science, Independent University Bangladesh (IUB), Dhaka, 1229, Bangladesh. Her research interests include artificial intelligence in higher education, IoT, and STEM education, cybersecurity.

Mst. Tahmina Jerin Arju is a researcher affiliated with MSc, Department of Computer Science, Independent University Bangladesh (IUB), Dhaka, 1229, Bangladesh. Her research interests include machine learning, artificial intelligence, Internet of things (IoT), cybersecurity.

Mahady Hasan is a Senior Associate Professor, Asian University for Women, Chattogram 4000, Bangladesh. His research interests include Engineering Education and Innovation, Software Engineering, Sustainable Intelligent.

Farzana Sadia is a faculty member, Department of Computer Science & Engineering, Independent University Bangladesh (IUB), Dhaka, 1229, Bangladesh. Her research interests include Software Engineering, Cloud Computing.

Shipra Banik is a Professor, Department of Computer Science & Engineering, Independent University Bangladesh (IUB), Dhaka, 1229, Bangladesh. Her research interests include Statistical Inference, Soft Computing Models, Statistical Modeling and Planning, Ridge Regression Analysis.

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APPENDIX

Table 2

Measurement Items.

Construct	Measurement Item	Definition	Instrument	Sources
ICT Self-Efficacy	ICT SE1 ICT SE2 ICT SE3 ICT SE4	An individual's perceived capacity to successfully use Information and Communication Technology (ICT) to accomplish specific tasks or solve problems. Esiyok et al. (2025)	I believe I can successfully use ICT tools to accomplish my academic tasks before actual classes.	Esiyok et al. (2025)
Technology-Based STEM Education	TBSE1 TBSE2 TBSE3 TBSE4	A learning method that merges STEM using digital tools, platforms, and applications to enhance student engagement and understanding. Esiyok et al. (2025)	I find it beneficial to engage in STEM education through technology-based learning platforms before actual classes.	Esiyok et al. (2025)
Perceived Ease of Use	PEU1 PEU2 PEU3	The intensity of personal belief is that using a particular technology or system will be effortless and free from difficulty. Esiyok et al. (2025)	I feel that using this technology is easy for me before actual classes.	Esiyok et al. (2025)
Perceived Usefulness	PU1 PU2 PU3	The perceived degree to which an individual expects a given technology will improve their performance or productivity. Esiyok et al. (2025)	I believe this technology will enhance my learning and understanding before actual classes.	Esiyok et al. (2025)
Enhanced Performance Expectation	EPE1 EPE2 EPE3	The belief that adopting a particular technology will lead to improved efficiency, effectiveness, or achievement of goals. Obiwuru (2024)	I expect my academic performance to improve by using this technology before actual classes.	Obiwuru (2024)
Intention to Use AI Chatbots	IUAC1 IUAC2 IUAC3	The willingness or likelihood of an individual to adopt and engage with AI-powered chatbots for specific tasks or learning purposes. Obiwuru (2024)	I intend to use AI chatbots for learning assistance before actual classes.	Obiwuru (2024
Actual AI Chatbot Usage	AACU1 AACU2 AACU3	The real, measurable interaction and engagement with AI chatbots for various applications, such as learning support, customer service, or problem-solving. Lee et.al (2022)	I regularly use AI chatbots to support my studies before actual classes.	Lee et.al (2022)
Self-Directed Learning with Technology	SDLT1 SDLT2 SDLT3 SDLT4	A learning approach in which individuals take initiative in acquiring knowledge and skills using digital tools and resources, often at their own pace and preference. Roca et.al (2024)	I take the initiative to learn new concepts using technology before actual classes.	Roca et.al (2024)
Technology Acceptance and Learning Motivation	TA & LM1 TA & LM2 TA & LM3	The relationship between a user's willingness to adopt technology and their motivation to learn, forced by factors such as PU, ease of use, and personal goals. Roca et.al (2024)	I feel motivated to learn when I accept and use new technology before actual classes.	Roca et.al (2024)
Perceived Convenience	PC1 PC2 PC3	The degree of user-perceived associated with a technological platform or system is accessible, time-saving, and easy to use in their daily activities. Ayanwale et. al (2024)	I find it convenient to use technology to support my learning before actual classes.	Ayanwae et. al (2024)

